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Assessment of algal farm designs using a dynamic modular approach

Jared M. Abodeely [a], André M. Coleman [b], Daniel M. Stevens [a], Allison E. Ray [a], Kara G. Cafferty [a], Deborah T. Newby [a,*]

[a] Biofuels and Renewable Energy Technology, Idaho National Laboratory, Idaho Falls, ID 83415, United States
[b] Hydrology Technical Group, Pacific Northwest National Laboratory, Richland, WA 99352, United States

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ABSTRACT

The notion of renewable energy provides an important mechanism for diversifying an energy portfolio, which ultimately would have numerous benefits including increased energy resilience, reduced reliance on foreign energy supplies, reduced GHG emissions, development of a green energy sector that contributes to economic growth, and providing a sustainable energy supply. The conversion of autotrophic algae to liquid transportation fuels is the basis of several decades of research to competitively bring energy-scale production into reality; however, many challenges still remain for making algal biofuels economically viable. Addressing current challenges associated with algal production systems, in part, requires the ability to assess spatial and temporal variability, rapidly evaluate alternative algal production system designs, and perform large-scale assessments considering multiple scenarios for thousands of potential sites. We introduce the development and application of the Algae Logistics Model (ALM) which is tailored to help address these challenges. The flexible nature of the ALM architecture allows the model to: 1) interface with external biomass production and resource assessment models, as well as other relevant datasets including those with spatiotemporal granularity; 2) interchange design processes to enable operational and economic assessments of multiple design configurations, including the integration of current and new innovative technologies; and 3) conduct trade-off analysis to help understand the site-specific techno-economic trade-offs and inform technology decisions. This study uses the ALM to investigate a baseline open-pond production system determined by model harmonization efforts conducted by the U.S. Department of Energy. Six sites in the U.S. southern-tier were sub-selected and assessed using daily site-specific algae biomass productivity data to determine the economic viability of large-scale open-pond systems. Results show that costs can vary significantly depending on location and biomass productivity and that integration of novel dewatering equipment, order of operations, and equipment scaling can also have significant impacts on economics.

1. Introduction

Biofuels provide a critical component in a renewable energy portfolio, primarily because of the growing demand for sustainable, renewable, and reduced-emission liquid transportation fuels. Autotrophic microalgae provide a promising alternative to conventional fossil fuels in part due to their versatility in growth media and growing conditions, the variety of strains available to satisfy locally-available resources and environmental conditions [1], their high-density growth per unit area [2], high lipid content [3], and their ability to provide a variety of different fuel end-products including drop-in fuels [4]. In addition, a number of key policy issues are addressed including reductions in GHG emissions [5], wastewater remediation [6–8], potential non-compete with food resources [9], increased national energy independence and security, and strengthening rural economics and the green energy market. Microalgae processing and conversion can also produce valuable co-products, including ethanol, methane, fertilizer, livestock feed, and co-firing [10], though it should be noted that these characteristics are highly dependent upon the strain of microalgae, how it was grown, and the processes used for harvest and dewatering. Third generation feedstocks or "energy crops," which include microalgae, have been shown to provide reduced emissions relative to diesel-derived petroleum sources while remaining non-toxic and biodegradable [11–13].

These benefits, however, come with challenges of sustainable resource use, in terms of water, land, CO_2, nutrients, and required infrastructure [14–17]. Significant technological and engineering challenges need to be addressed in order to achieve required energy-scale production as well as making this energy resource economically feasible and cost competitive with petroleum-based fuels [2,18]. Nonetheless, under the U.S. Energy Independence and Security Act (EISA) of 2007,

* Corresponding author at: Biofuels and Renewable Energy Technologies, Idaho National Laboratory, P.O. Box 1625, Idaho Falls, ID 83415, United States. Tel.: +1 208 526 7779; fax: +1 208 526 3150.
E-mail address: Deborah.Newby@inl.gov (D.T. Newby).

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the Renewable Fuels Standard (RFS) mandates the production and use of 36 billion gallons per year (BGY) of renewable fuels by 2022, of which 5 BGY are to be derived from advanced fuels and biodiesel [19].

One of the challenges of assessing algal production systems is the temporal and spatial variability of biomass productivity and the impact that this variability has on the economics of converting microalgae to biofuels. Evaluating long periods of record (~30-years) allows for the consideration of extreme meteorological events and patterns which directly influence the economics of biomass production. There have been numerous studies investigating the feasibility of commercial microalgae production facilities, but a majority of these studies are limited to a specific location or use broad biomass productivity assumptions to perform regional assessments. To our knowledge, existing techno-economic assessment (TEA) models lack the ability to efficiently and inherently assess algal production systems around local variability. This paper describes the Algae Logistics Model (ALM), an integrated, techno-economic, spatiotemporally-aware system dynamics and data management system that is comprised of a design configuration of operation modules that evaluate the capacity, throughput, mass balance, energy requirements, performance, and economics via capital expenditures (CapEx) and operational expenditures (OpEx) at fine spatial and temporal scales. The ALM stems from another modeling effort, the Biomass Logistics Model (BLM) which focuses on terrestrial feedstock supply systems [20]. The ALM is built using a modular framework, thus providing the required analysis flexibility to address current challenges by evaluating a suite of design, equipment, and operation scenarios. The flexible nature of the ALM architecture allows the model to: 1) interface with external biomass production and resource assessment models, as well as other relevant datasets including those with spatiotemporal granularity; 2) interchange design processes to enable operational and economic assessments of multiple design configurations, including the integration of current and new innovative technologies; and 3) conduct trade-off analysis to help understand the site-specific techno-economic and inform technology decisions. Furthermore, with the ability to interface with advanced biophysical-based production and resource assessment models such as those found in the Biomass Assessment Tool (BAT), thousands of sites can be evaluated with relatively little effort [13,15,16].

Several prior feasibility studies have been performed using microalgae for bioenergy production [3,21,22]. These studies assessed microalgae cultivation for biofuel and biogas production using available engineering and biological technologies. The economic viability of the systems varied based on biomass productivity and the algal production system design assumptions. Assessments were limited to a single site and therefore did not consider the spatial constraints of the proposed design. Recent modeling efforts demonstrate various pathways for cultivating and converting microalgae to bioenergy [13,22–26]. These assessments address many of the existing challenges associated with making microalgae a viable resource for bioenergy production.

Richardson et al. [24] performed an assessment using a Monte Carlo simulation that relied upon several key input variables, including evaporation rate, water cost, water depth, days of operation, cost of algal growth medium, carbon dioxide, algae production rate, and algal oil content. The assessment included two hypothetical scenarios of commercial-scale microalgae farms. The first scenario used data collected from literature, while the second scenario used data collected from a 0.2-ha experimental algal farm in the Southwestern United States. Both scenarios assumed 405 ha of open pond with microalgae biomass productivity ranging from 20–30 g/m^2-day to 18–25 g/m^2-day and a lipid content ranging from 20–40% to 40–60%, respectively. “Scenario 1” assessed a production window of 10 months/year with an average production of nearly 21,400 L_{oil}/ha-year, while “Scenario 2” assumed a continuous growth environment producing over 42,600 L_{oil}/ha-year. The study concluded that costs are highly variable due to inherent risks in producing biofuel from microalgae.

Zamalloa et al. [25] performed a techno-economic assessment using microalgae to produce methane to generate electricity through anaerobic digestion. Many capital and operating expense assumptions were derived from the Benneman and Oswald [27] report. Three studies using constant daily productivity were conducted to assess the viability of algal biomass as a resource for biogas production. Sensitivity analysis was performed considering several factors. While the study did not investigate microalgae for biofuel, it is important to recognize other pathways for producing energy from microalgae, especially using methods that could be integrated into algal farms to produce power and help reduce overall costs of producing algal biofuels.

In 2011, Davis et al. [23] performed a techno-economic study on autotrophic microalgae for open-pond and photobioreactor systems. The study used a process simulation model to perform mass and energy balances to evaluate the two algal production systems. A top-down approach was taken by first setting a biofuel production goal and then, based on biomass productivity and farm operating assumptions, determining the infrastructure required to produce the biofuel target. For the open-pond scenario, a steady-state simulation was performed assuming a daily algae biomass productivity of 25 g/m^2-day with a lipid content of 25% and an operation window of 330 days per year. The process simulation model was used to simulate a microalgae facility producing 10 MM gal/year of biofuel requiring a facility footprint of over 2900 ha, with an open-pond area representing approximately 1950 ha of the facility total. The study determined that triacylglycerol (TAG) could be sold for $8.52/gal and that the price could be further reduced by using co-products onsite or selling them in the open-market.

Sun et al. [26] performed a comparative analysis of existing studies that explored the cost of producing TAG. The comparative analysis included U.S. DOE national laboratories, industry, and academia. These studies included a diverse range of assumptions and end products. As a result of this diversity, the cost associated with obtaining TAG varied significantly. Sun et al. used a normalized set of input assumptions for the previous studies and was able to reduce economic variability with cost ranging from $10.87/gal to $13.32/gal.

Recently, the U.S. DOE's Bioenergy Technologies Office began an initiative to harmonize existing modeling efforts across its national laboratories [28]. Existing techno-economic, resource assessment, and life-cycle analysis models were coordinated to establish a conservative baseline algal production system design. The harmonized effort enabled quantification of cost, greenhouse gas emissions, and resource requirements using consistent infrastructure and operating assumptions from cultivation through biodiesel production. In-depth discussion of the original techno-economic, resource assessment and life-cycle models can be found in Davis et al. [23], Wigmosta et al. [13], and Frank et al. [29], respectively. The harmonized effort assessed several scenarios for the 5 BGY goal including a steady state and seasonal productivity scenario. Potential suitable algal farms within a region around the U.S. Gulf Coast were clustered and the average productivity was assessed. The cost of biodiesel between clusters varied as much as $3.50/gal, demonstrating the direct impact spatial variability can have in algal production systems. Another assessment investigated the impacts of using steady-state productivity versus dynamic variability driven by seasonal climatic conditions. Assessments using the seasonal scale increased the cost of biodiesel by nearly $1.00/gal, therefore demonstrating the impact of temporal variability within algal production systems.

While these studies contribute to overcoming existing barriers in microalgae fuel production, they do not address the temporal and spatial dynamics at the fidelity needed to assess large numbers of individual algal production system sites, such as the ~90,000 potential unit farm pond sites identified by Wigmosta et al. [13]. Understanding the impacts of temporal and spatial variability on production cost is important to the viability of algal biofuel production. Furthermore, the ability to assess and integrate new processes and technologies for assessment into an algal production system design can be challenging. The ALM presented in this paper provides a mechanism to address temporal and spatial variability while enabling assessment of multiple scenarios that incorporate new, innovative technologies and for open pond design configurations.

2. Model and methodology

2.1. Algae Logistics Model

The motivation behind the development of the ALM was derived from the current limitations of existing TEA models to assess algal production systems. These limitations include the ability to: 1) rapidly assess alternative algal production system designs including the use of multiple algal strains; 2) perform automated large-scale assessments considering multiple design and multiple strain selections for thousands of potential sites; and 3) assess both spatial and temporal variability and trade-offs of multiple scenarios.

The ALM is a compilation of process simulation modules (Fig. 1) developed in a system dynamics software package (PowerSim™) and is arranged to allow user-defined configurations and initialization of static and/or variable parameters as is required. The modular design approach provides flexibility in tailoring a system design to local environment and economic dependencies, specific equipment types and sizes, capacity and throughput, and/or final end product(s). The ALM includes an internal database comprised of data from the National Agricultural Statistical Service (http://www.nass.usda.gov), Bureau of Labor Statistics (http://www.bls.gov/data/), and vendor information of equipment specifications. The streaming of the system processes through mass and energy outputs and returns, accumulate and adjust through the system and ultimately achieve OpEx and CapEx for the site and design of interest. Because of the model's inherent ability to modify system designs, parameter sensitivity analysis can be implemented to understand the strengths, weaknesses, and impacts of a particular system configuration as well as individual components within the design [20]. The modules within the ALM are programmatically assessed at the process level, and high-fidelity process module results are aggregated, in time- and process-space, to provide an overall assessment of the algal production system design. The ALM also includes an external C++ based software controller that interfaces with PowerSim™ to initialize process module parameters, advance the user-defined time-step, iterate through the modules for the duration of the simulation, and run for multiple sites (Fig. 1). The baseline configuration of the ALM is based on the prior-referenced U.S. DOE model harmonization effort [28] which draws together parameters and assumptions from a number of studies [29–36].

A core capability within the ALM is its consideration and handling of a multi-faceted logistics space that controls the management and movement of 'materials'. The logistical sub-types within the ALM address: 1) information; 2) process and production; and 3) required physical resources. First, from within the model itself, the management and flow of information, including physical materials, energy, and expenses, are explicitly handled where dynamic process states are accepted as inputs from upstream components, processed according to established parameters, rule sets, and environment conditions, then passed to the next downstream process at each time-step. The information logistics are highly dynamic so as to handle process and component changes within the modeled production system without having to change any aspect of how information is retrieved and passed through the system. Second, the process and production aspects of the model, and representation thereof, are handled where the logistics domain space is within the production system itself. The capability is brought forth by the inherent ability to join process system components (i.e., flocculation to centrifugation to solvent-based lipid extraction or sedimentation to centrifugation to apparatus-based lipid extraction) and dynamically add capacity, including associated capital and operational expenses, to individual components to meet required material flow demands. The production logistics within the ALM allow for analyzing the quantity of materials passing through the value chain in order to optimize capital efficiency and production capability. Lastly, the more commonly regarded aspect of logistics involves the management and movement of physical resources from an origination point to a location of need. For the ALM, these include the external required resources to operate a production facility, specifically including water, nutrients, and CO_2, and explicitly considering the availability, quantity and delivery expenses. The external physical resources provide the starting point for evaluating the process chain at a given site and helping to determine site feasibility. While the ALM can internally handle resource logistics based inputs, these are derived from published material, industry practice or expert opinion. To garner spatiotemporally explicit logistics-based resource inputs, the ALM was designed to accept time-series inputs from the BAT model where the nearest and most acceptable resource availability is identified and transported using graph-theory based least-cost routing [13,16]. This ultimately provides, at an individual site, not only the required quantity of material based on current time-step environment conditions, but also the cost, and transport energetics.

2.1.1. Model inputs

Key time-varying inputs to the ALM include site-specific algal biomass productivity, evaporative water loss, and CO_2 and nutrient (N and P) demand. User-defined static model inputs include lipid fraction and unit pond size. Additionally, inputs for the number of unit ponds at a site, the land value, expenses of site preparation and production site delivery of water, nutrients, and CO_2 can be included as static or spatially-varying values. The model time-period is simply established

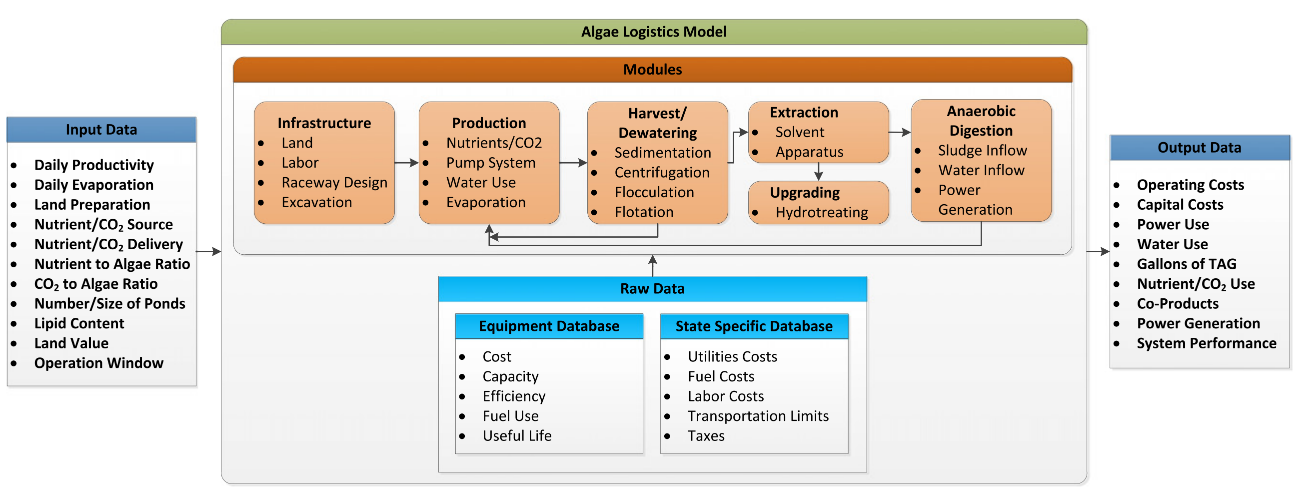

Fig. 1. Graphical representation of the process simulation. Key inputs and outputs from the ALM and the underlying databases.

by the bounds of records included in the key time-varying inputs. Being driven by the algal production system design, the ALM queries its internal database tables to retrieve equipment cost parameters and performance specifications for each module in the design. Site-specific data is also retrieved from the internal database to pull local constraints and costs for elements such as labor rates, maintenance and insurance, and tax and regulation data [20]; however, these values can also be overridden with static values if the user has more relevant information or wants to run sensitivity analyses in this regard. The collection of input and internally-accessible data, along with user-specified initial conditions for a given site are processed through the ALM to ultimately deliver a time- and process-aggregated cost assessment for the given design. In addition, ALM tracks and outputs specific user-configured process/equipment CapEx and OpEx, mass and energy, and requirements for infrastructure, water, nutrients, pumps, harvest/dewatering, extraction, upgrading, anaerobic digestion, transportation, power consumption and more (Fig. 2). The process-specific level of granularity allows for an assessment of resource, cost, and energy barriers to better understand where design improvements are required and can be made.

2.1.2. Process streams

The ALM was developed to allow for an adaptive flow of data through the model framework using a “plug-and-play” approach. This allows for the dynamic interchange of information amongst the

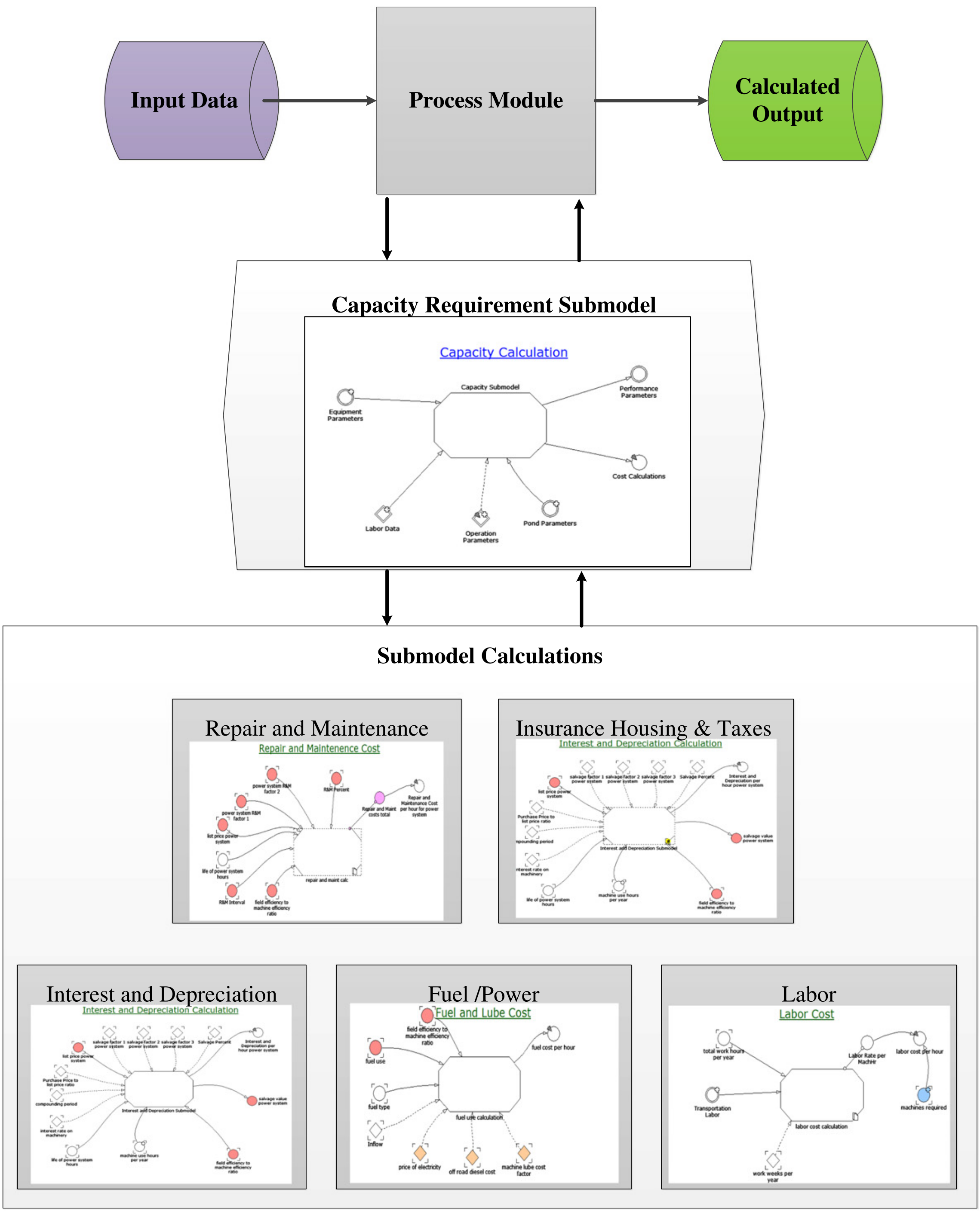

Fig. 2. Schematic depicting the process-specific level.

user-defined process modules, no matter which process steps and equipment are added or removed. Process module constants can be initialized through user input or accepted with the model defaults. Time-varying data, such as biomass growth and evaporative water loss, is read in at a user-specified time-step and will have an effect through the full system as it is propagated through downstream process modules. The ALM initializes the downstream parameters for each process module based on the output from the upstream process. For example, the equipment and number of units of equipment required to harvest and dewater the biomass are determined based on the volumetric flow rate which changes at each process step as additional water is removed. The operation modules process the inflow streams according to the equipment's capacity and performance parameters. The output streams are then passed to the next downstream process and so on until the sequence of processes for the given time-step is complete. Energetics and operational expenses associated with running the equipment is determined at each process-step and is preserved for the individual processes, as well as aggregated through the system for each time-step. The mass balances of the various streams (i.e., biomass, water, nutrients, and carbon) are managed at the individual process modules and are propagated and tracked throughout the system. For example, as part of the sedimentation process in the baseline ALM configuration, the majority of the water and a small fraction of algal biomass are routed back to the pond, whereas the majority of the algae and the remaining water are forwarded on to the flocculation process (Fig. 3). The separation of the mass from the sedimentation to the flocculation process is tracked and balanced throughout the model and is reflected in the number of equipment units required (i.e., CapEx) and associated energy required for pumping, equipment operations, maintenance, etc. (i.e., OpEx).

2.1.3. Equipment scaling

Throughout the model and through each time-step, equipment units for the individual processes are added to the production system, as required to meet the biomass production demand and process of the associated flow of material. The addition of individual units is dictated when volumetric flows, as a function of biomass productivity, exceed the capacity and throughput specifications defined in the internal equipment database along with the number of units already added to the individual process. Although individual equipment units are accumulated as required for the model time-series, each process module will only operate the minimum number of equipment units required to meet the demand for the time-step, otherwise, non-operationally required equipment units remain idle. This approach brings in some cost-efficiencies for the overall system OpEx in terms of energy savings and other associated operational expenses. Conversely, assessing CapEx at peak production rates could create additional expenses to the system due to the limited number of days that the peak biomass production occurs. For this reason, additional analysis on optimal site scaling, to determine trade-offs between additional equipment and production potential, has been explored in a follow-on study [37].

2.1.4. Resource recycling

The ALM includes a recycling feedback mechanism that considers major nutrients (N and P), algal biomass, carbon, and water. For each of these process streams, model-defaults or user-defined loss rates are specified and reduced against the total mass and put back in at the top of production stream for use at the beginning of the next time-step (for example, see Fig. 3 for water and algal biomass recycling). In the baseline ALM design configuration, the biomass stream from the lipid extraction process is sent to an anaerobic digester to produce biogas (methane) for power production which is then credited towards the total process energy consumption and associated OpEx. The effluent stream leaving the anaerobic digester is recycled back to the pond providing assumed bioavailable nutrients and carbon back to the system and thus reducing the total new resource requirements, and associated OpEx, for the subsequent time-step. In addition to process loss rates, nutrients (N and P) and CO_2 resource requirements are established with user-defined stoichiometry to establish demand as a function of biomass productivity. The baseline ALM configuration uses the demand ratios established in Williams and Laurens [36] that set the C:N:P to 175:21:1 and the ash-free dry weight biomass composition to protein: 0.47, polysaccharides: 0.28, and lipid: 0.25 and is consistent with the U.S. DOE harmonization study [28].

2.1.5. Production cost assessment

The ALM performs production cost assessments of the algal production system design and outputs the time- and process-aggregated CapEx and OpEx per gallon of TAG. The production cost assessments are performed and maintained for each process in the system over the model time-series, as well as being aggregated throughout the entire configured system. CapEx are determined by the infrastructure and equipment required to process the material through the process module based on the equipment's capacity. Cost multipliers are applied to

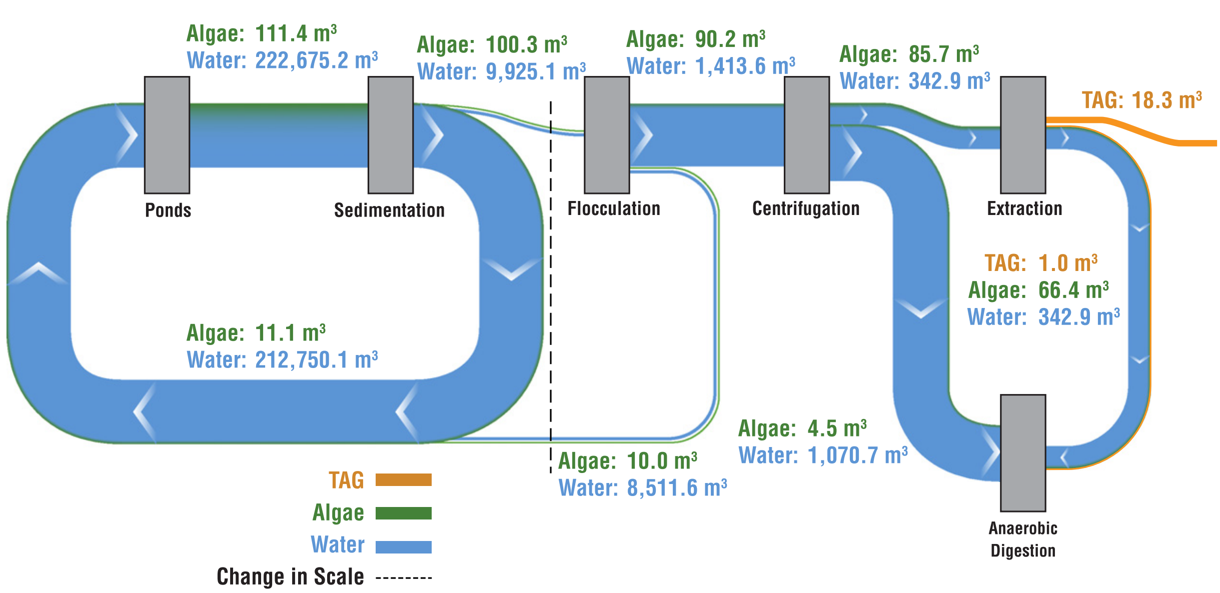

Fig. 3. A modified Sankey flow diagram tracking the volume of water, algae and TAG through a variety of ALM process modules, where the width of the stream is proportional to the volume of each component.

cover the expense of various aspects associated with acquiring and installing the equipment including engineering, overhead, administration, insurance, and permitting. Overhead cost assumptions were derived from ANL et al. [28] and Davis et al. [23]. OpEx represents the expenses associated with the daily activity of running the algal production system. This includes water, nutrient and CO_2 requirements, various process materials for dewatering, anaerobic digestion, and extraction and power requirements for the individual processes. As an example, the ALM explicitly considers the operating water expense into the system, recognizing that this is a resource that can be recycled and used in a variety of capacities. Thus, water from the harvesting and dewatering steps is recycled back to the cultivation ponds. The on-site pumping power requirements are factored into the OpEx and control the total energy cost for bringing new makeup water onsite, whether this is by local groundwater well pumping or pumping from a surface water supply via pipeline [16]. In concert with the U.S. DOE harmonization study [28], the baseline ALM configuration sends the lipid-extracted slurry along with the centrifuge supernatant to the anaerobic digester, for which power generation credits are brought to the production system's OpEx. The OpEx are calculated on a daily time-step based on the material throughput, the quantity of equipment required to process the material throughput, and the equipment's performance, in terms of capacity and throughput, in processing the material.

2.2. Productivity and resource assessment

Algal biomass production data and resource requirement and availability represent several of the key inputs into the ALM and can vary significantly over space and time [13,15,16,18,38]. As a result, TEA models must be able to capture spatial and temporal variability and assess the impacts of this variability on the operation of algal production systems. This is particularly important when driving towards planning and facility siting at energy scales where the evaluation of regional and national potentials must come together to meet production targets in the most economical way possible. Within the ALM, default static biomass production and resource requirement values are available to initialize biomass productivity parameters. While this approach is suitable for performing sensitivity analyses on different design configurations, it will likely not capture the temporal and spatial variability of a specific site or regional/national sites of interest. For this reason, the ALM was designed to interface with GIS-based resource analysis models and datasets, such as those found in the BAT [13,15,16], which are able to provide the spatiotemporal biomass productivity data and inputs for other resource requirements.

The meteorological patterns around a potential site will have a significant impact on annual microalgal biomass productivity. Seasonal variations and extreme weather conditions determine the number of productive growth days. The BAT is a spatiotemporal resource analysis and production assessment modeling suite developed at the Pacific Northwest National Laboratory and performs high-resolution, national-scale assessments including potential biomass production for multiple algal strains, land resource suitability and availability, land value and site preparation costing, water requirements, supply sources and routing, and more [13,15,16]. The core models within BAT are 1) a full mass and energy balance hydrodynamic model to determine pond temperature and evaporative water loss [39]; and 2) an in-house developed biophysical biomass growth model that uses time-varying pond temperature and incoming solar radiation along with biomass growth parameterizations that include optimal, sub-optimal, minimum and maximum temperature ranges, photo conversion efficiency, bioaccumulation efficiency, light utilization efficiency, biomass energy content, lipid content, and oil density [13]. These core models are driven by 30-years of hourly local meteorological data to determine biomass production potential and evaporative water losses. While the models simulate pond temperature and biomass growth at an hourly time-step in order to capture diurnal effects, the daily growth is averaged over the daylight hours and populated to a time-series file that is accessible by other models. The land suitability analysis is a GIS-based model within the BAT used to determine land resource availability to identify non-sensitive areas for potential algal production systems and is documented at length in Wigmosta et al. [13]. A unit algal production system is defined as 405 ha of open ponds and 80 ha of associated infrastructure. The Wigmosta et al. [13] study identified over 11,000 contiguous suitable areas (~90,000, 485-ha unit farms) within the conterminous United States.

3. Results and discussion

In order to demonstrate the utility of the modular and dynamic design of the ALM, site-specific inputs from the BAT-generated national resource assessment were passed into the model for several different candidate sites around the U.S. Analyses were performed using varying ALM design configurations to assess the impacts of equipment/module substitution and ordering of processes within the system.

First, as a case study, the harmonized baseline algal production system design established by the U.S. DOE [28] was simulated within the ALM for six locations across the conterminous United States: Tampa, Florida; Mobile, Alabama; Greenville, North Carolina; Brownsville, Texas; Las Cruces, New Mexico; and Imperial, California. For these analyses, site-specific algal biomass productivity values were passed into the ALM from the BAT. Variability of algal productivity at the six selected sites, sourced from modeled hourly daylight production values to a mean daily average, were assessed using the long-term mean annual, long-term mean daily and absolute minimum and maximum daily production values over a period of 30-years (Fig. 4). Comparison of the long-term daily and annual trends in production at the various demonstrates the importance of factoring in spatiotemporal variability in algal productivity when designing infrastructure. This is particularly true for downstream processing equipment in order to minimize the amount of expensive capital equipment sitting idle during periods of time with reduced production. It stands to reason that sites with greater variability should be scaled more closely to the annual production capacity than to peak capacity; whereas, scaling to maximum capacity at sites with limited variability in biomass productivity offers an improvement to production system economics.

Fig. 5 shows the average cost per gallon of TAG at each of the six study sites when systems are configured to handle peak production (maximum) capacity over the 30-year simulation, as well as when the systems are scaled to the 30-year average annual productivity. For these analyses, daily productivity data was passed into the model, and daily operating expenses were assessed based on algae, water, nutrient, and process material throughput. CapEx are assessed based on the infrastructure required to handle the throughput of each process during either peak or annual average production. For algal production scenarios scaled to the 30-year average annual productivity, system costs were reduced in all cases with cost reductions ranging from \$0.38 to \$3.48/gal_{TAG} depending on the site. Considering these results along with the site-specific variability in productivity (Fig. 4), the correlation between production variability and scaling (30-year long-term daily average versus the single maximum production value over the same time period) is evident. For example, modeled costs at the Imperial, California site (based on inputs using 30-year long-term daily averages) illustrate that only a modest cost savings (\$0.37/gal_{TAG}) is achievable relative to the maximum capacity scenario for a site with limited temporal variability. However, at sites with significant temporal variability, such as Las Cruces, New Mexico, scaling based upon 30-year long-term daily averages represents a substantial cost savings (\$3.48/gal_{TAG}). These analyses demonstrate the potential value of scaling based on site production variability.

While production variability clearly plays a role in the economic viability of algal biofuels, another key biological variable is lipid content. The Tampa, Florida location was selected as a model site to explore impacts of productivity in concert with varying degrees of lipid content on

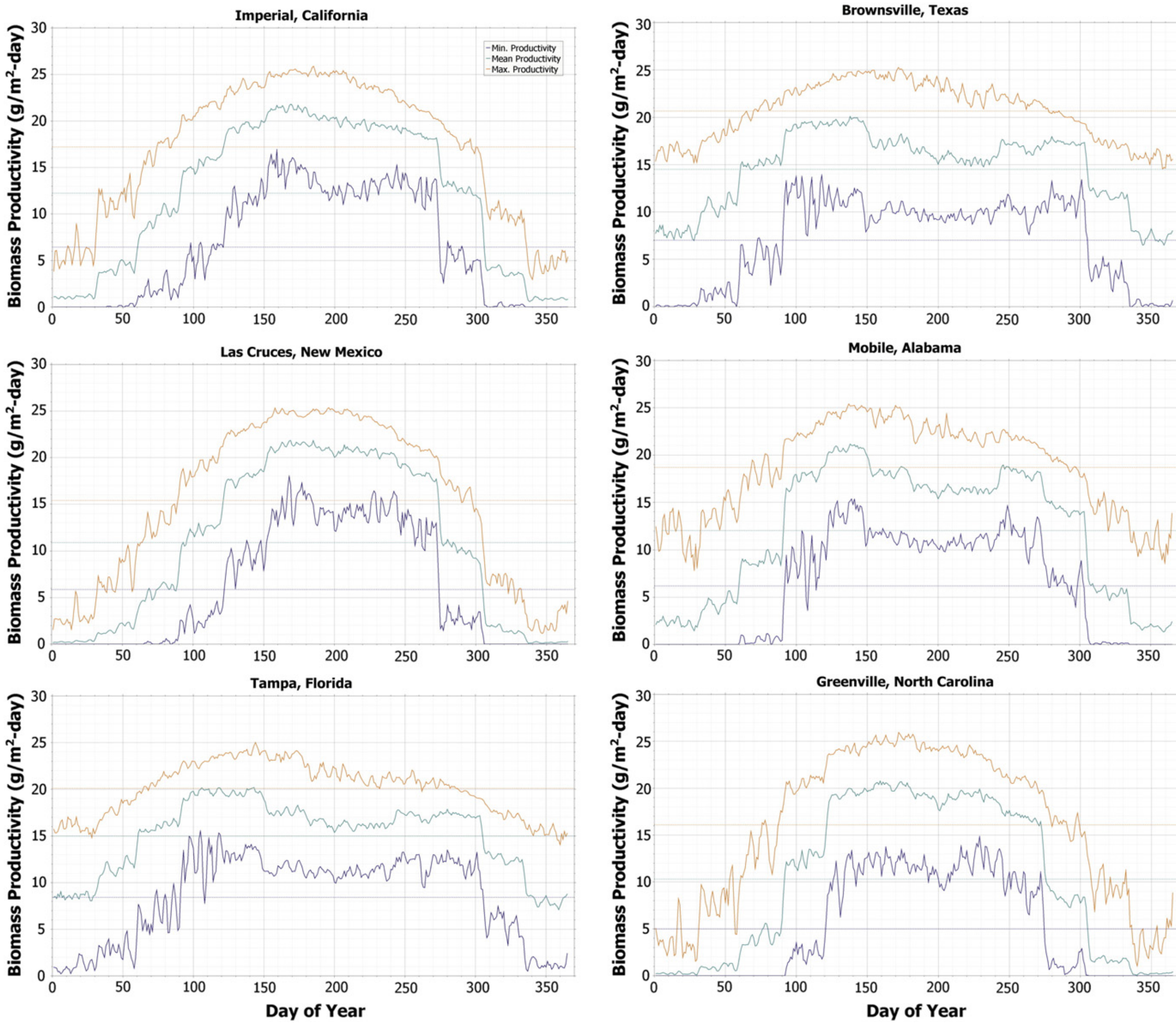

Fig. 4. Simulated daily algal productivity variability for six locations investigated in this study.

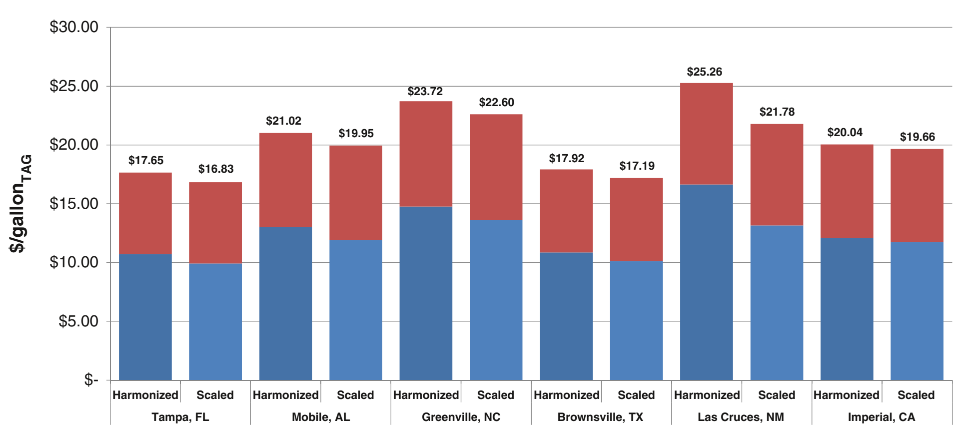

Fig. 5. Investigation of appropriate scaling of algal production systems using the harmonized baseline design and BAT algal biomass productivity based on a system at 30-year peak biomass productivity or 30-year average biomass productivity.

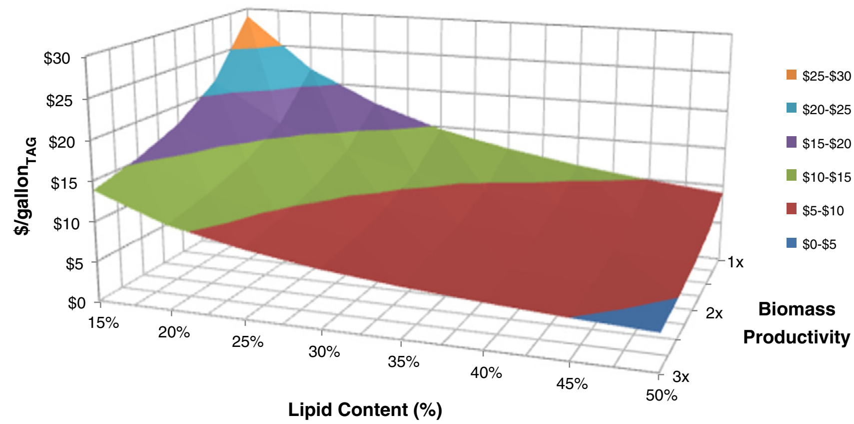

Fig. 6. This 3-D plot demonstrates the expected cost reduction per gallon of TAG produced as a function of increasing biomass productivity and lipid content, where 1× is the baseline.

algal biofuel economic feasibility, specifically as a function of $/gal of TAG. Fig. 6 simulates the cost of TAG production as a function of theoretical biomass productivity and lipid content using the harmonized baseline algal production system design [28]. The baseline productivity scenario used BAT-provided daily values with no multiplier (1×) under maximum capacity scaling assumptions, which uses the highest modeled production value observed over 30-years to determine equipment scaling requirements (see Fig. 4, long-term maximum). A total of 40 scenarios were run: BAT-provided daily biomass productivity was increased and assessed for up to 3 times (3×) the baseline scenario in increments of 0.5×, and lipid content was assessed in 5% increments from 15 to 50%. Increases in productivity and lipid content were considered since the intent of the analysis was to see if cost targets could be met solely through bio-engineering an algal strain with high-productivity and capable of high lipid accumulation. Results show that biological enhancements to microalgae alone are not sufficient to reduce the cost of using microalgae for biofuel production. Advancements in engineering to existing technologies or development of new, innovative technologies will be required.

The ALM provides the ability to explore potential impacts of new and innovative technologies. For example, the Tampa, Florida location was used to demonstrate the value of the modular structure of the ALM to: 1) explore two algal system design alternatives that incorporated a new, innovative dewatering technology developed by an industry partner; and 2) address design constraints that may arise due to microalgae strain selection. While the results themselves are informative, the real value herein is the demonstration of the inherent modularity of the ALM structure through equipment substitution and ordering of operations. Several microalgae currently being investigated for biofuel production would not be efficient in the existing baseline design due to challenges with autoflocculation, and, as a result, alternative dewatering technologies must be considered. In the present study, we consider a low-energy, chemical-free, continuous-flow harvesting system that is capable of harvesting directly from the cultivation system and dewatering up to 95% solids content as an alternative to traditional dewatering technologies. The specifics of the novel dewatering technology are proprietary, but the general approach involves electroflocculation to induce clumping, followed by electrolysis within a holding tank, allowing small bubbles of hydrogen and oxygen to carry the flocks to surface where they concentrate and can be harvested by mechanical means. The first design assumed that the selected algal strain would not autoflocculate efficiently, and therefore, the alternative dewatering technology module was used to replace the three-stage dewatering modules of the baseline design. The second design assumed that the algal strain being investigated could autoflocculate and used sedimentation as a primary harvesting step. The alternative dewatering technology was applied after sedimentation replacing flocculation and centrifugation to further dewater the microalgae from 1 to 20% solids. This takes advantage of the low-cost sedimentation process and the low-energy dewatering technology to reduce costs. For each case, the open-pond infrastructure, productivity, and lipid content remain constant. Table 1 summarizes the design scenarios investigated in this study.

In the first design, the alternative dewatering technology was used for the entire dewatering process and had higher CapEx relative to the baseline algal production system design, however, exhibited lower OpEx. The higher CapEx are due to the number of alternative dewatering technology units required to process the throughput for a 405-ha algal production system, though collectively, they are more energy efficient than the U.S. DOE harmonization design [28]. In the second design, sedimentation served as the primary harvesting step, and thus less total volume needed to be processed by the alternative dewatering technology. In this case, CapEx were essentially the same, and OpEx were lower compared to the baseline algal production system design (Fig. 7). It is important to note that these particular analyses were run using novel dewatering equipment designed for laboratory-scale operations and do not reflect anticipated expenses when

Table 1
Scenario comparison between the harmonized and alternative algal system designs.

Process	Harmonized Design	Alternative Design 1	Alternative Design 2
Infrastructure	Earthwork and installation of open-pond infrastructure		
Cultivation	Daily biomass productivity (g/m^2-day)		
Dewatering	Sedimentation–autoflocculation in settling tank to 1% solids (10 g/L) DAF — chemical flocculation with collection by DAF to 6% solids (60 g/L) Centrifugation — concentrate to 20% solids (200 g/L)	Alternative dewatering technology — concentrate to 20% solids (200 g/L)	Sedimentation–autoflocculation in settling tank to 1% solids (10 g/L) Alternative dewatering technology — concentrate to 20% solids
Extraction	High pressure homogenizer Liquid–lipid extractor		
Anaerobic digestion	Methane production via biomass/water; digestate solid for fertilizer, effluent stream recycled		

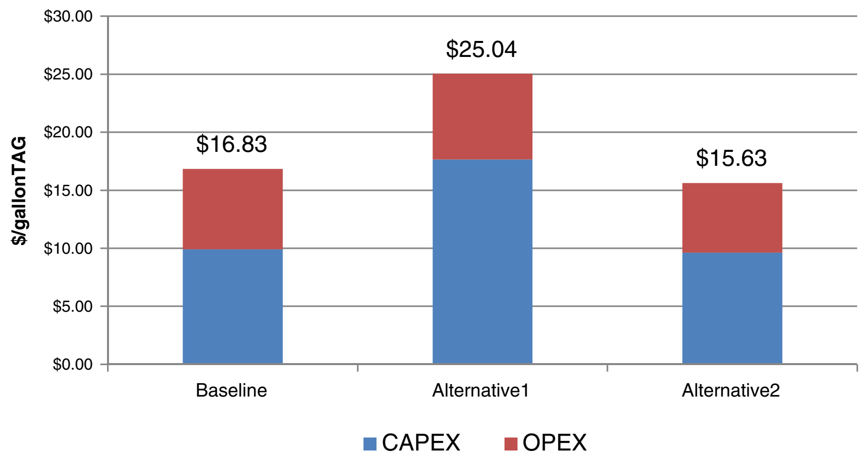

Fig. 7. Capital and operating costs of alternative designs as compared to harmonized baseline design.

equipment, designed for large-scale operations, are used. Since the time of these analyses, our industry partner has developed larger scale equipment in order to reduce the number of units and expense required to harvest an equivalent volume. The larger scale equipment uses the same general approach for harvest, but as is the case when processes are scaled, the larger scale equipment involved a significant engineering redesign. As dewatering technologies evolve and improvements in other processes merge, the modular configuration of the ALM can be leveraged to evaluate these design scenarios.

4. Conclusions

Biofuels, specifically biodiesel derived from microalgae, have received significant interest as an alternative to conventional fossil fuels due to growing concerns regarding climate change, global energy demands, and the need for energy independence. Models capable of assessing the temporal and spatial aspects of large-scale production are paramount to understanding commercial- and energy-scale costs and operation. The value of the model developed here has been demonstrated through assessments of scaling based on site specific productivity, concurrent analyses of impacts of lipid content and productivity on cost, as well as analysis of emerging technologies and impact of ordering and processing as compared to a baseline design. The ability of the ALM to interface with site-specific resource assessment data allows for temporal and spatial assessments to be made, thus providing the opportunity to identify the ideal system design given the local conditions and algal strain(s) of interest. Moreover, the ALM enables the assessment of multiple biomass productivity scenarios across thousands of potential algal production sites to determine the best possible scenario and economic feasibility of the algal production system to exist and operate. Because process modules can be added, removed, or interchanged to better understand how technologies perform within a specific system, the ALM facilitates integration of emerging technologies and investigation of alternative ordering of production system processes.

The ALM was used to assess several scenarios. Results showed that spatial and temporal variability can significantly impact the cost of producing biofuel from microalgae. Results also demonstrated that further investigation of scaling of algal production systems is needed to determine the optimal size and configuration for potential sites. Assessment of theoretical algal strains with enhanced biomass production and lipid content showed that further cost reductions are needed and will have to come from low cost, low-energy technologies. Lastly, an innovative, alternative dewatering technology from an industry partner was assessed and shows potential for reducing OpEx associated with dewatering the microalgae. While many other TEA models can also conduct similar analyses, the modular and dynamic design of the ALM, as well as its ability to interface with spatiotemporal resource assessment data, allow for the efficient computation and analyses of many thousands of regional or national sites in one model run, makes it a valuable tool for analysis of multiple dynamic design scenarios.

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References

[1] C.S. Jones, S.P. Mayfield, Algae biofuels: versatility for the future of bioenergy, Curr. Opin. Biotechnol. 23 (2012) 346–351.
[2] DOE, National Algal Biofuels Technology Roadmap, Biomass Program, U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, 2010.
[3] J. Sheehan, T.G. Dunahay, J.R. Benemann, P.G. Roessler, J.C. Weissmann, A Look Back at the U.S. Department of Energy's Aquatic Species Program-Biodiesel From Algae, National Renewable Energy Laboratory, 1998. 1–328.
[4] M.Y. Menetrez, An overview of algae biofuel production and potential environmental impact, Environ. Sci. Technol. 46 (2012) 7073–7085.
[5] X. Liu, B. Saydah, P. Eranki, L.M. Colosi, B. Greg Mitchell, J. Rhodes, A.F. Clarens, Pilot-scale data provide enhanced estimates of the life cycle energy and emissions profile of algae biofuels produced via hydrothermal liquefaction, Bioresour. Technol. 148 (2013) 163–171.
[6] W.J. Oswald, C.G. Golueke, Biological transformation of solar energy, Adv. Appl. Microbiol. 11 (1960) 223–242.
[7] G. Torzillo, B. Pushparaj, J. Masojidek, A. Vonshak, Biological constraints in algal biotechnology, Biotechnol. Bioprocess Eng. 8 (2003) 338–348.
[8] J.B.K. Park, R.J. Craggs, A.N. Shilton, Wastewater treatment high rate algal ponds for biofuel production, Bioresour. Technol. 102 (2011) 35–42.
[9] M. Hannon, J. Gimpel, M. Tran, B. Rasala, S. Mayfield, Biofuels from algae: challenges and potential, Biofuels 1 (2010) 763–784.
[10] B. Wang, Y.Q. Li, N. Wu, C.Q. Lan, CO_2 bio-mitigation using microalgae, Appl. Microbiol. Biotechnol. 79 (2008) 707–718.
[11] D. Bajpai, V.K. Tyagi, Biodiesel: source, production, composition, properties and its benefits, J. Oleo Sci. 55 (2006) 487–502.
[12] J. Sheehan, V. Camobreco, J. Duffield, H. Shapouri, M. Graboski, K.S. Tyson, An Overview of Biodiesel and Petroleum Diesel Life Cycles, National Renewable Energy Laboratory, 2000.
[13] M.S. Wigmosta, A.M. Coleman, R.J. Skaggs, M.H. Huesemann, L.J. Lane, National microalgae biofuel production potential and resource demand, Water Resour. Res. 47 (2011) W00H04 (13 pp.).
[14] C.E. Canter, The Sustainability of Biofuels Produced From Microalgae, The University of Arizona, Tucson, Arizona, 2013.
[15] E.R. Venteris, R.L. Skaggs, A.M. Coleman, M.S. Wigmosta, An assessment of land availability and price in the coterminous United States for conversion to algal biofuel production, Biomass Bioenergy 47 (2012) 483–497.
[16] E.R. Venteris, R.L. Skaggs, A.M. Coleman, M.S. Wigmosta, A GIS cost model to assess the availability of freshwater, seawater, and saline groundwater for algal biofuel production in the United States, Environ. Sci. Technol. 47 (2013) 4840–4849.
[17] J. Yang, M. Xu, X. Zhang, Q. Hu, M. Sommerfeld, Y. Chen, Life-cycle analysis on biodiesel production from microalgae: water footprint and nutrients balance, Bioresour. Technol. 102 (2011) 159–165.

[18] R.C. Pate, Resource requirements for the large-scale production of algae biofuels, Biofuels 4 (2013) 409–435.
[19] EISA, Energy Independence and Security Act (EISA) of 2007, 110th Congress of the United States of America, Washington D.C., USA 2007, 2007.
[20] K.G. Cafferty, D.J. Muth, J.J. Jacobson, K.M. Bryden, Model based biomass system design of feedstock supply systems for bioenergy production, ASME International Design Engineering Technical Conference & Computers and Information in Engineering Conference, ASME, Portland, OR, 2013.
[21] J.R. Benemann, R.P. Goebel, J.C. Weissman, D.C. Augenstein, Microalgae as a Source of Liquid Fuels, EnBio, Inc., Fairfield, CA, 1982. 1–229.
[22] T.J. Lundquist, I.C. Woertz, N.W.T. Quinn, J.R. Benemann, A Realistic Technology and Engineering Assessment of Algae Biofuel Production, Energy Biosciences Institute, University of California, Berkeley, California, 2010.
[23] R. Davis, A. Aden, P.T. Pienkos, Techno-economic analysis of autotrophic microalgae for fuel production, Appl. Energy 88 (2011) 3524–3531.
[24] J.W. Richardson, J.L. Outlaw, M. Allison, The economics of microalgae oil, AgBioforum 13 (2010) 119–130.
[25] C. Zamalloa, E. Vulsteke, J. Albrecht, W. Verstraete, The techno-economic potential of renewable energy through the anaerobic digestion of microalgae, Bioresour. Technol. 102 (2011) 1149–1158.
[26] A. Sun, R. Davis, M. Starbuck, A. Ben-Amotz, R. Pate, P.T. Pienkos, Comparative cost analysis of algal oil production for biofuels, Energy 36 (2011) 5169–5179.
[27] J.R. Benemann, W.J. Oswald, Systems and Economic Analysis of Microalgae Ponds for Conversion of CO_2 to, Biomass, 1996. 1–201.
[28] ANL, NREL, PNNL, Renewable diesel from algal lipids: an integrated baseline for cost, emissions, and resource potential from a harmonized model, Argonne, IL: Argonne National Laboratory; Golden, CO: National Renewable Energy Laboratory; Richland, WA: Pacific Northwest National Laboratory, 2012.
[29] E.D. Frank, J. Han, I. Palou-Rivera, A. Elgowainy, M.Q. Wang, ANL Report on Life-Cycle Analysis of Algal Lipid Fuels, Argonne National Laboratory, 2011. 1–99.
[30] N. Uduman, Y. Qi, et al., Dewatering of microalgal cultures: a major bottleneck to algae-based fuels, J. Renewable Sustainable Energy 2 (012701) (2010) 1–15.
[31] W.W.F. Leung, Industrial Centrifugation Technology, McGraw-Hill, New York, 1998.
[32] N. Nagle, P. Lemke, Microalgal fuel production processes: analysis of lipid extraction and conversion methods, extract from Bollmeier, W. et al. Aquatic Species Program Annual Report, 1989, (http://www.nrel.gov/docs/legosti/old/3579.pdf).
[33] D. Humbird, et al., Process design and economics for biochemical conversion of lignocellulosic biomass to ethanol, NREL Technical Report, 2011, (http://www.nrel.gov/docs/fy11osti/47764.pdf).
[34] R.W. Harris, M.J. Cullinane Jr., et al., Process Design and Cost Estimating Algorithms for the Computer Assisted Procedure for Design and Evaluation of Wastewater Treatment Systems (CAPDET), EPA, 1982.
[35] G. Tchobanoglous, F.L. Burton, et al., Wastewater Engineering: Treatment and Reuse, McGraw-Hill, Boston, 2003.
[36] P.J.l.B. Williams, L.M.L. Laurens, Microalgae as biodiesel & biomass feedstocks: review & analysis of the biochemistry, energetics & economics, Energy Environ. Sci. 3 (5) (2010) 554–590.
[37] A.M. Coleman, J.M. Abodeely, R.L. Skaggs, W.A. Moeglein, D.T. Newby, E.R. Venteris, M.S. Wigmosta, An integrated assessment of location-dependent scaling for microalgae biofuel production facilities, Algal Res. (5) (2014) 79–94.
[38] J.C. Quinn, K.B. Catton, S. Johnson, T.H. Bradley, Geographical assessment of microalgae biofuels potential incorporating resource availability, Bioenergy Res. 6 (2) (2013) 591–600.
[39] W.A. Perkins, M.C. Richmond, MASS2, Modular Aquatic Simulation System in Two Dimensions: Theory and Numerical Methods, PNNL-14820-1, Pacific Northwest National Laboratory, Richland, WA, 2004.